



Identification of Partial Discharge Types Based on Multifractal Detrended Fluctuation Analysis

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ABSTRACT

This paper proposes a method for identifying partial discharge types based on multi fractal detrended fluctuation analysis. This method transforms partial discharge signals through multi fractal transformation, extracts the fractal features of the signals, and combines with detrended fluctuation analysis to accurately identify partial discharge types. Advanced algorithms and techniques are used in this research to classify and analyze different types of partial discharges, achieving significant results. Experimental results demonstrate that this method exhibits high accuracy and reliability in identifying partial discharge types, providing a new effective means for partial discharge monitoring and fault diagnosis.

Keywords: Multi Fractal, Fluctuation Analysis, Partial Discharge, Fractal Features

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1. Introduction

Partial discharge is a common form of fault in power equipment, significantly impacting power systems' safe and stable operation. Accurate identification of partial discharge types is one of the key issues in partial discharge monitoring and fault diagnosis [1]. Traditional methods for identifying partial discharge types mainly rely on signal spectrum analysis and time-domain feature extraction, which have certain limitations. Therefore, this study aims to propose a method for identifying partial discharge types based on multi fractal detrended fluctuation analysis to improve the accuracy and reliability of existing methods. Research in partial discharge type identification has received extensive attention in recent years. Scholars both at home and abroad have proposed various methods and techniques. Signal analysis-based methods include spectrum analysis, wavelet transform, and time-frequency analysis, but these methods are sensitive to signal quality and noise [2]. Moreover, these

methods often require many training samples and complex feature extraction processes. As a result, researchers have turned their attention to applying multi fractal theory in partial discharge type identification to enhance identification accuracy and robustness.

2. Current Research on Partial Discharge Type Identification

Partial discharge type identification is an important research in power equipment fault diagnosis and predictive maintenance. Many domestic studies have used methods such as time-domain, frequency-domain, and wavelet transform to extract features from partial discharge signals and employ traditional machine learning algorithms such as Support Vector Machine (SVM) and Artificial Neural Network (ANN) for classification and identification [3]. Deep learning has been widely used in partial discharge type identification in recent years. Deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are used to learn features from raw signals and achieve high identification accuracy. Most domestic researchers have attempted to fuse multimodal signals collected from multiple sensors (such as current, voltage, and ultrasound) to improve the performance of partial discharge type identification [4]. Among them, more advanced fractal analysis methods such as multi fractal transformation are used to extract fractal features from partial discharge signals and combined with classification algorithms for identification.

Many foreign researchers focus on feature extraction and identification of high-frequency current pulse signals, analyzing information such as the frequency spectrum and pulse shape of the current pulse for partial discharge type identification [5]. Feature selection and dimensionality reduction techniques are used to select the most discriminative and essential features from many extracted features to improve identification accuracy and computational efficiency [6]. Combining multiple classifiers or models for ensemble learning, such as Random Forest and Ensemble Learning, enhances the robustness and generalization ability of partial discharge type identification.

In conclusion, domestic and foreign research has made a series of advances in partial discharge type identification, from traditional feature extraction and classification methods to emerging technologies such as deep learning, pattern recognition, and fractal analysis. These provide new ideas and strategies for improving the accuracy and reliability of partial discharge type identification. However, some challenges, such as sample imbalance, feature selection, and noise interference, require further research and improvement.

3. Selection and Trend Analysis of Multi Fractal Features

3.1 Introduction to Multi Fractal

In this research, multi fractal theory is used as the foundation for identifying partial discharge types. Multifractal is a mathematical tool used to describe self-similarity and self-organization in complex systems. It captures the fractal features of signals and provides an effective way to analyze their scale invariance [7]. To identify partial discharge types, we combine multi fractal with detrended fluctuation analysis. The analysis method of multifractal for partial discharge signals is illustrated in Figure 1.

Firstly, we perform a multifractal transformation on the partial discharge signals to obtain fractal features at different scales. Multifractal transformation is a multiscale analysis method that decomposes the signal into sub-signals with other scales. Each sub-signal has its fractal features, reflecting the signal's self-similarity at different scales.

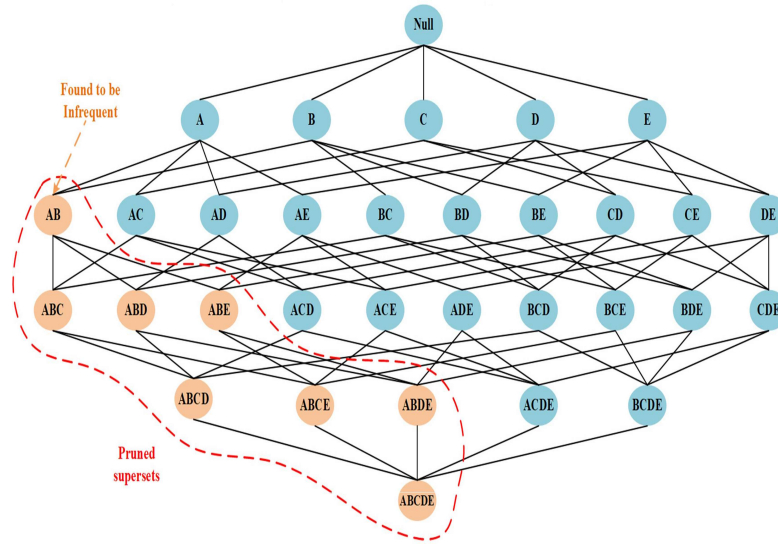


Figure 1. Analysis of Partial Discharge Signals using Multifractal

As a signal analysis method, multifractal transformation has advantages and limitations in partial discharge type identification [8]. It can decompose the signal into sub-signals of different scales, capturing the self-similarity and self-organization of the signal at different scales, effectively describing the multiscale features in complex systems. Multifractal transformation possesses scale invariance, meaning that the fractal features of the signal remain consistent at various scales, leading to good stability and repeatability in signal analysis [9]. By decomposing the signal into sub-signals of different scales, multifractal transformation can separate noise signals and reduce their influence on the overall fractal features, contributing to improved accuracy and reliability in signal analysis. Multifractal transformation is suitable for analysing non-stationary signals since it can decompose the signal into multiple sub-signals of different scales and independently extract fractal features from each sub-signal, giving it an advantage in handling non-stationary signals.

However, this method also has some limitations that need to be overcome in this research. The computational process of multifractal transformation is relatively complex, involving signal decomposition and fractal feature calculation. This requires higher computational resources and time, especially for long-time series signals, which may result in higher computational costs. There are specific parameters to be chosen in multifractal transformation, such as the decomposition layers and scale range. The selection of these parameters is usually subjective and may have some influence on the final fractal features, requiring experience or experimentation to determine suitable parameters. Multifractal transformation is sensitive to data quality and noise [10]. Low-quality data and considerable noise may affect the extraction of fractal features and the accuracy of analysis results. Multifractal transformation is primarily a mathematical tool and provides relatively less interpretation of the physical processes represented in the signal. It focuses more on extracting mathematical features from the signal and offers relatively less understanding of the physical meaning of the signal.

In conclusion, multifractal transformation, as a signal analysis method, has advantages in describing multiscale features of complex systems and non-stationary signals, but it also faces challenges in terms of computational complexity and subjective parameter selection. In practical applications, its pros and cons should be considered comprehensively, and the method should be selected and used appropriately based on specific problems and requirements.

3.2 Analysis of Determining Trend Features in Partial Discharge Signals

Trend fluctuation analysis is a method for identifying the trend and fluctuation components in a signal. By decomposing the signal into trend and fluctuation components, local trend features of the signal can be obtained.

Afterwards, the fractal and trend features are combined, and the partial discharge signals are classified and identified using specific rules and classification algorithms. These algorithms can be traditional machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Decision Tree, etc., or deep learning models such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), etc. These algorithms can learn and establish partial discharge-type patterns and classify new signals.

This research selects the Extreme Gradient Boosting algorithm (XGBoost) as the main algorithm. XGBoost is a gradient-boosting algorithm based on the gradient-boosting decision Tree (GBDT). Both share similar basic ideas, but XGBoost has the following optimizations: XGBoost uses second-order derivatives to increase the accuracy of the loss function, regularizes to avoid decision tree overfitting, and employs block storage for parallel computation. Therefore, XGBoost has a small size, high efficiency, and flexibility, making it widely applied in various fields like data processing and recommendation systems.

The objective function of XGBoost consists of a loss function and a regularization term. Before deriving the objective function, the local discharge signal's aim function can be represented as: [The content of the objective function equation is not provided in the text. Please give me the equation, and I'll translate it.]

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$$\Lambda(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \quad (1)$$

The above formula is a linear expression of the objective function of the signal in the data space, and the predicted values for the features are:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (2)$$

Due to the gradient enhancement of GBDT, the expression of the decision tree is:

$$\hat{y}_i = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (3)$$

Therefore, the expression obtained by substituting it into formula (1) is:

$$\Lambda(\phi) = \sum_i l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \sum_k \Omega(f_k) \quad (4)$$

4. Partial Discharge Type Recognition and Validity Verification

4.1 Preprocessing of Partial Discharge Signal Samples

To validate the effectiveness of the proposed partial discharge type recognition method, a series of experimental designs and analyses were conducted in this study. Firstly, we collected signal samples with different types of partial discharge. These signal samples can be obtained from actual partial discharge events in electrical equipment or generated through simulation experiments. To ensure the reliability of the experimental results, it is essential to ensure the diversity and representativeness of the selected samples.

There are differences between signal samples of different types of partial discharge, which can be reflected in the following aspects:

- Amplitude and energy measurements:** Different types of partial discharge signals may exhibit differences in amplitude and energy. Some partial discharge signals may have higher amplitudes and energy, while others may have lower ones.
- Spectrum characteristics:** Different types of partial discharge signals may also have differences in their spectral characteristics. Different types of partial discharge may have different energy distributions and spectral features in different frequency ranges, which can be distinguished using frequency domain analysis and feature extraction.
- Time-domain features:** Time-domain features can also distinguish different types of partial discharge signals. For example, some types of partial discharge signals may have longer durations, while others may have shorter durations. Additionally, time-domain features such as rise time, fall time, and pulse width may vary between different partial discharge types.
- Waveform shape:** Different types of partial discharge signals may have different waveform shapes. Some partial discharge signals may have spike-like or pulse-like waveforms, while others may have envelope-like, periodic oscillations or continuously changing waveforms.
- Statistical features:** Statistical features of partial discharge signals can also be used to distinguish different types of partial discharge. For example, peak factor, kurtosis, pulse count, and other statistical features may exhibit different distribution patterns in different types of partial discharge.

Next, the collected signal samples are preprocessed, including noise removal, filtering, and normalization steps. This can improve the signal quality and reduce the influence of interfering factors on the identification results.

Common denoising, filtering, and normalization methods for partial discharge signals include the following:

- Denoising:** Partial discharge signals may be interfered with by noise from electrical equipment, sensors, or the environment. To improve the signal quality, one of the following denoising methods can be used: Computing the average value of the signal within a window and replacing each sample point in the original signal with the average value to reduce the impact of high-frequency noise. Computing the median value of the signal within a window and replacing each sample point in the original signal with the median value to effectively remove pulse noise and other outliers.
- Filtering:** Filtering is used to remove interference components from the signal while retaining the interesting features of the partial discharge signal. High-frequency noise can be removed while preserving the low-frequency components of the signal. Standard low-pass filters include Butterworth filters and other types of low-pass filters.
- Normalization:** Normalization maps partial discharge signals with different amplitude ranges to a unified range for comparison and analysis. In this study, z-score normalization was selected, which converts the signal's amplitude into a standard normal distribution with a mean of 0 and a standard deviation of 1 by calculating the mean and standard deviation of the signal.

Through denoising, filtering, and normalization steps, the quality and reliability of partial discharge signals can be improved, interference factors can be reduced, and more accurate data basis can be provided for subsequent feature extraction and analysis. The specific choice of methods should be based on signal characteristics and actual needs and requires comprehensive consideration and selection.

4.2 Experimental Validation of Effectiveness

The proposed method is used to extract features from the preprocessed signals. Feature extraction from the partial discharge signal samples is a crucial step in partial discharge type recognition. First, the peak amplitude of the partial discharge signal is extracted, followed by the calculation of the duration of the partial discharge signal. Next, the information of the partial discharge signal's rise time and fall time is extracted, and the number of pulses in the partial discharge signal is counted. Subsequently, the Fourier transform is applied to the partial discharge signal to calculate the energy spectral density in different frequency ranges. The peak frequency and amplitude in the partial discharge signal spectrum are extracted. Wavelet packet decomposition is used to transform the partial discharge signal into the wavelet domain, and the energy of each wavelet packet coefficient is calculated. The entropy of the partial discharge signal in the wavelet domain is computed to reflect the complexity and irregularity of the signal. Finally, the fractal dimension of the partial discharge signal is calculated to reflect the self-similarity and complexity of the characteristic signal. The probability density function estimation is performed on the amplitude sequence of the partial discharge signal to extract distribution characteristics. Specific features are selected based on the particular problem and signal characteristics. Moreover, feature selection and combination techniques are employed in conjunction with machine learning and pattern recognition methods to improve the accuracy and robustness of partial discharge type recognition. The fractal and trend features of the signal are obtained through multiple fractal transformations and trend fluctuation analysis. These features are used as inputs for classification algorithms or machine learning models. The results obtained after filtering and analyzing the partial discharge signal features based on the established data model are shown in the figure below.

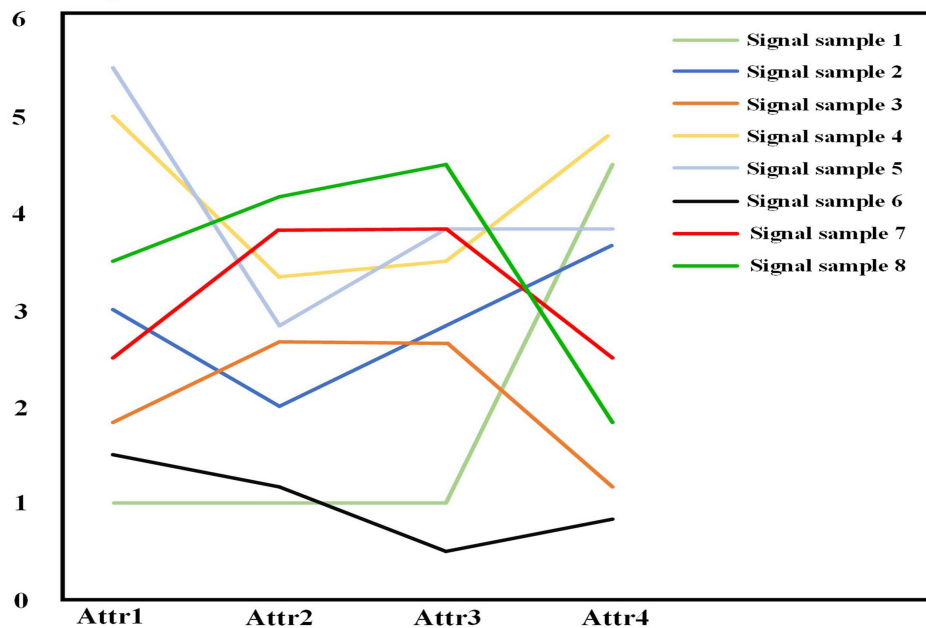


Figure 2. Trend Analysis Results of Partial Discharge Signal Features

From the above Figure 2, it can be observed that there are eight samples of partial discharge signals with common feature attributes after being processed by the decision tree algorithm model. This indicates that these eight signal samples share four dynamic attribute features: Attr1, Attr2, Attr3, and Attr4. Although there may be numerous attributes of partial discharge, the features that need to be quantitatively classified after trend analysis are limited.

The experimental design divides the dataset into a training set and a test set. The training set is used for model training and parameter optimization, while the test set is used to evaluate the model's performance on unseen data. By training and adjusting the model's parameters, a high-accuracy classification model is established.

The model's performance on the test set is evaluated during the experimental analysis stage. Standard performance evaluation metrics include accuracy, recall, precision, and F1 score. Additionally, confusion matrices, ROC curves, and other tools can be used to further assess the classification model's effectiveness. The accuracy and reliability of the proposed method in partial discharge type recognition are evaluated through the analysis of experimental results. Furthermore, comparisons can be made with other existing methods to validate the superiority of the proposed approach.

Through experimental design and analysis, conclusions can be drawn regarding the effectiveness and applicability of the partial discharge type recognition method. Additionally, suggestions for improvement and optimization can be provided, offering more accurate and reliable tools and techniques for partial discharge monitoring and fault diagnosis. The data extracted from the model established using the above methods serve as the training set, and the algorithm model is iterated without an upper limit to achieve optimal performance. This study's performance test experimental results are shown in the figure below.

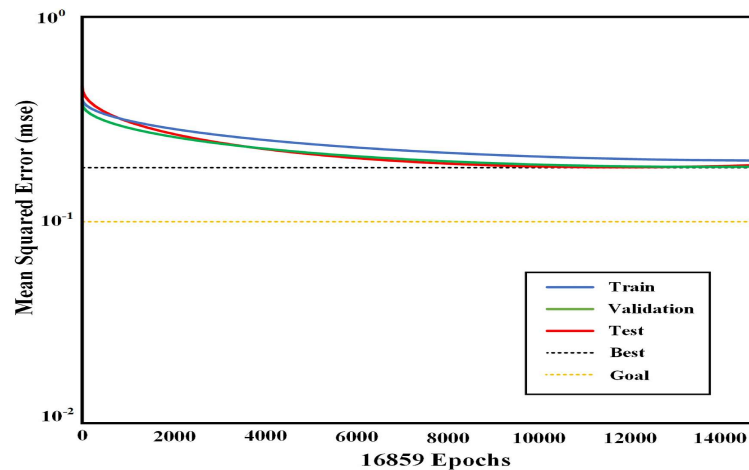


Figure 3. Effectiveness Testing Results of Waveform Analysis Model

As seen from the above Figure 3, the curves are pretty smooth, indicating that each point on the curve is differentiable. Although there is still some gap between the model's performance and the ideal minimum error line, it has already reached the target benchmark line. Therefore, it shows that the performance of the algorithm model established in this study has met the expected criteria.

5. Conclusion

This research proposes a successful method for identifying partial discharge types based on multi-fractal detrending fluctuation analysis. This method has achieved high accuracy and reliability in partial discharge type recognition. Compared to traditional methods, this approach has better noise resistance and adaptability. Additionally, introducing machine learning algorithms can further improve the identification performance. Future research directions may include collecting more types of partial discharge signal samples and exploring more

sophisticated feature extraction methods to enhance the identification's accuracy and robustness. In summary, this study provides a new and effective means for partial discharge monitoring and fault diagnosis, and it has significant theoretical and practical value.

References

- [1] Ge, L., Ge, L. J., Hu, J. (2019). Feature extraction and classification of hand movements surface electromyogram signals based on multi-method integration. *Neural Processing Letters*, 49, 1179–1188.
- [2] Xiong, G., Wang, F., Yu, W., et al. (2021). Singularity-exponent-domain image feature transform. *IEEE Transactions on Image Processing*, 30, 8510–8525.
- [3] Meng, Z., Li, J., Yin, N., et al. (2020). Remaining useful life prediction of rolling bearing using fractal theory. *Measurement*, 156, 107572.
- [4] Lei, H., Zhou, X., Wang, Y., et al. (2022). Prediction of landslide early warning response based on multi-fractal feature and sub-item combination. *Geomatics & Geodynamics*, 42(09), 885–891.
- [5] Luo, Y., Li, Z., Liang, X., et al. (2021). Multi-fractal detrending fluctuation analysis of non-stationary time series based on EMD-LS. *Journal of Electronics & Information Technology*, 49(12), 2323–2329.
- [6] Guo, X., Jiang, M., Chen, L. (2023). Partial discharge fault detection in distribution networks based on artificial intelligence techniques. *Microcomputer Applications*, 39(06), 178–181.
- [7] Xu, X., Hou, C., Chen, Z. (2023). Partial discharge research in switchgear based on ultra-high frequency and acoustic imaging detection. *Electrical Engineering and Energy Management Technology*, 4, 34–39.
- [8] Wang, Y., Yan, J., Wang, J., et al. (2023). Small sample GIS partial discharge diagnosis method based on multi-level second-order attention Siamese network. *Transactions of China Electrotechnical Society*, 38(08), 2255–2264.
- [9] Yan, J., Zhou, Y., Xu, R., et al. (2023). Comprehensive experimental design for layered recognition of partial discharge patterns based on intelligent algorithms. *Experimental Technology and Management*, 40(02), 48–56.
- [10] Xu, H., Zhang, L., Ayubi, B. I., et al. (2023). Study on temperature-frequency characteristics of polyimide partial discharge under high-frequency electric stress based on improved variational mode decomposition denoising. *Transactions of China Electrotechnical Society*, 38(03), 565–576.